EOID Evaluation and Automated Target Recognition

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LONG-TERM GOALS

The Navy is in the early stages of incorporating high resolution Electro-Optic IDentification (EOID) sensors into shallow water littoral zone minehunting systems on towed, remotely operated, and autonomous platforms. These downlooking laser-based sensors operate at unparalleled standoff ranges in visible wavelengths to image and identify mine-like objects (MLOs) that have been detected through other sensing means such as magnetic induction and various modes of acoustic imaging.

Our long term goal is to provide a robust automated target cueing and identification capability for use with these imaging sensors. It is also our goal to assist the Navy in understanding, quantifying, and ultimately predicting the detection, identification, and false alarm performance of these systems in varied conditions of water quality, ambient light, and range to target.

OBJECTIVES

Our primary objective in CY02 was to evaluate the performance of critical elements of our algorithm suite over the extensive database of EOID imagery collected in the August 2001 EOID Evaluation field trials off the coast of Panama City, FL. Both target cueing and coarse classification algorithms were to be assessed as these would provide much of the functionality required for man-in-the-loop decision Aided Target Recognition. Also as part of this objective, we sought to relate performance measures to quantified and varied test conditions to gain a preliminary understanding of the limitations of EOID Laser Line Scan (LLS) systems as currently configured.

APPROACH

Mine cueing and natural and man-made object identification are mechanized through an algorithm architecture that combines proven Raytheon target cueing and object classification/identification approaches from other military applications with new Computer Vision techniques. This hybrid architecture and the legacy Raytheon efforts that were leveraged in its construction are shown in *Figure 1*. Investigators on these projects include: Dr. Alan Vanuga (model-based classifiers); Dr. Piali De (feature-based classifiers); Dr. Kamran Reihani (computer vision techniques), and Mr. Radzelovage (Airborne Standoff Minefield Detection System algorithm suite, including an MLO cuer).

Table 1 elaborates on the multiple paths available through this architecture based on the challenge presented by the test environment and the objective of the user. Throughout the four-year evolution of this approach, all three of the processing challenges in *Table 1* have been demonstrated at proof-of-principle levels. 2002 Efforts have focused on Challenge #1 with the goal of maturing the corresponding processing flow to achieve robust performance levels appropriate for tactical Navy operations. Henceforth, the discussions in this report will only address Challenge #1.

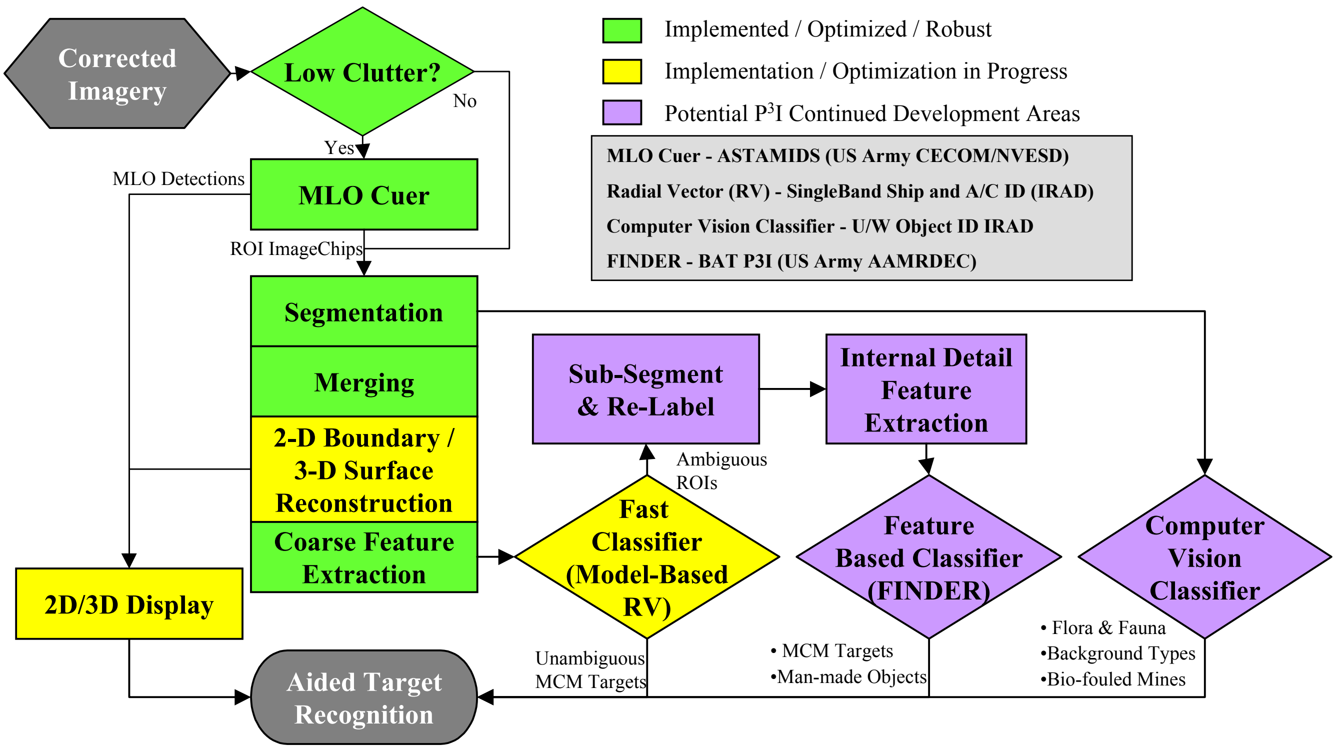

Figure 1: The Multi-Strategy AiTR Processing Flow leverages successful elements from multiple DOD-related efforts

Table1: The AiTR Processing Strategy adapts to the challenge and the user's objective

Implemented/Optimized/Robust (2-D) (green); Implemented/Optimization in Progress (yellow); Potential P3I Development Areas (purple) **Architecture Components Involved in Meeting MCM Challenges**	**CHALLENGE #1** Detect and ID non- or low-level biofouled MLOs in low cluttered or near noise limited environments such as those which are conducive to sonar detection and military craft landings.	**CHALLENGE #2** Detect and ID biofouled MLOs around which a local bio-environment has formed; detect and ID any MLOs within a challenging discrete clutter environment such as a reef or textured rocky bottom.	**CHALLENGE #3** Identify natural and man-made objects as well as natural background types in low-noise (near pristine) conditions for the purpose of automating benthic composition and environmental health studies.
MLO Cuer	Yes		
ROI Segmentation	Yes		
Image Segmentation		Yes	Yes
Merging	Yes	Yes	Yes
Pre-Screening	Yes	Yes	Yes
Boundary/Surface Reconstruction	Yes	Yes	Yes
Course Feature Extraction	Yes	Yes	Yes
3-D Display	Yes		
Model-Based Radial Vector Classifier	Yes	Yes	Yes
Sub-Segment and Re-Label		Yes	Yes
Internal Detail Feature Extraction		Yes	Yes
Feature-Based Classifier		Yes	Yes
Computer Vision Classifier		TBD	Yes

WORK COMPLETED

During the Key West Survey (Underwater Object Identification in Laser Line Scan Imagery) contract (Reference OP15 annual reports for CY1999 and CY2000), the multi-strategy processing architecture (*Figure 1*) was defined and the segmentation, region labeling, and preliminary computer vision components were implemented. In CY2001, the coarse (Radial Vector) classifier was incorporated and demonstrated and a MATLAB and PC/GUI-based tool suite was created to support algorithm development and to provide an integrated capability to review, ground-truth, process, and analyze the uniquely formatted raw imagery and ancilliary data recorded during sensor operations. Finally, an extensive data collection off Panama City, FL. was conducted in 2001 to support CY02 objectives.

In CY02, the tool suite was used to ground truth all of the Panama City test images containing MLOs and was automated to extract image quality metrics (e.g. signal-to-noise-plus-clutter) relating to each MLO and to the conditions under which it was imaged. The tool was then upgraded to exercise the algorithm suite over the entire data base to obtain performance estimates versus the quality metrics.

Multiple iterations of modifying and re-testing the algorithms against a subset of the database were conducted. Results were assessed at intermediate levels in the processing chain to understand and overcome the barriers to both object detection and to accurate boundary delineation - as is required for the Radial Vector Classifier. As this effort progressed, it was determined that multi-stage segmentation approaches used to segregate the image into all of its constituent components (discretes and statistical backgrounds), although critical for environmental characterization studies, would not be viable for nearer-term real-time mine detection/identification applications.

Consequently, a fast target cueing concept from Raytheon's ASTAMIDS program was employed and found to be highly effective at identifying MLOs across the broad range of S/(N+C) conditions encountered in the data set. The cuer steps are depicted in *Figure 2* and are as follows:

- *Mean Downsampling the Image to 6" Pixels* – provides for uncorrelated noise reduction, greatly reduces downstream thruput, and yields 20-60 pixels on target (POT), ideal for simple boundary analysis and shape discrimination

- *Sobel Edge Magnitude Filtering* – enhances edges in the scene and creates thick-walled outlines of any discrete objects that have reflectance contrast with respect to their immediate surroundings

- *Fill Factor (FF) Score Image* – assesses the degree to which local regions throughout the image possess locally strong edge patterns that form simply shaped objects whose boundaries can be approximated by an elliptical annulus. This processing is performed at every other pixel in the image

- *Peak/Mean Downsampled Fill-Factor Score Image* – by downsampling the FF Score image, spurious high scores are knocked down while strong extended responses are preserved. This provides for false alarm reduction while eroding extended responses down to a few pixels among which a single peak can be found.

- *Local FF Score Peak Image* – this processing finds all the local peaks within the Downsampled FF Score Image, reducing the likelihood of redundant "hits" (detections) on a given target.

- *Thresholded Peak Image* – The final stage in detection is to threshold the Local Peak FF Image. The threshold was determined as a tradeoff between detection probability and false alarm rate for an empirical data set (in our case, a subset of the Panama City, FL data). Identical thresholds as those used for ASTAMIDS were derived from the data set.

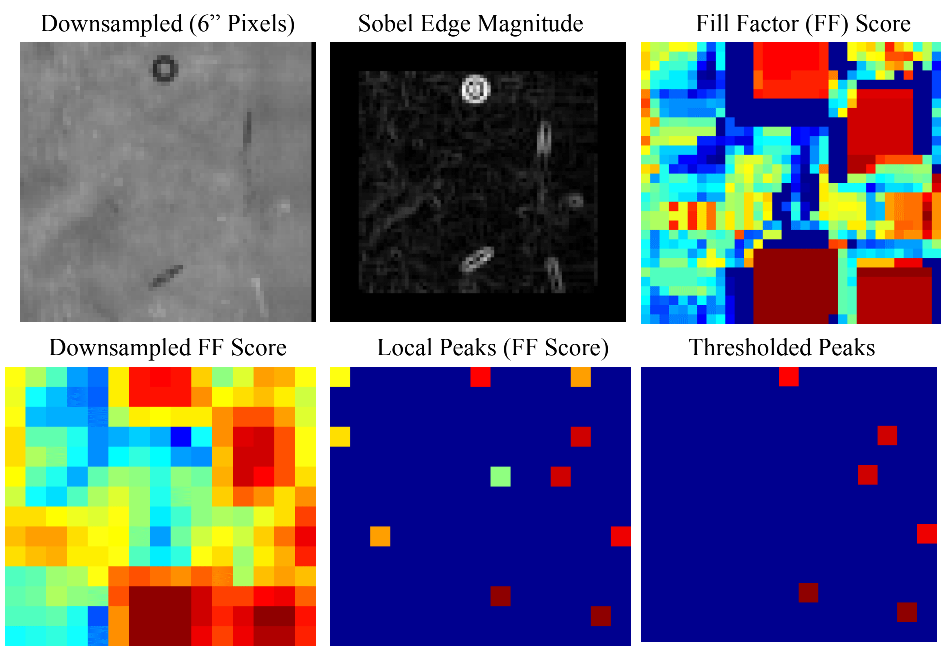

Figure 1: The six processing stages in the MLO cuer are shown to effectively detect all five man-made MLOs in the underwater scene

RESULTS

The Cuer was exercised versus the entire Raytheon LLS image database collected at Florida Bay off Panama City in August 2001. The database consisted of 231 images (1024 x 1024 pixels) containing over 600 MLOs, including mine simulants and man-made clutter. Most of the MLOs had significantly lower signal-to-noise-plus-clutter than the case illustrated in Figure 2 above, making detection challenging. The results of this testing are conveyed in the four graphs in *Figure 3*.

The upper left plot shows detection probability as a function of Edge-MAD (Mean Amplitude Difference of Edges). Edge-MAD is a degree-of-difficulty metric extracted from our ground truth tool and is defined as the absolute value of the average intensity difference between the object boundary pixels and those in their immediate background divided by the standard deviation of the intensity values in the local background. This metric is akin to the signal-to-noise-plus-clutter-ratio but correlates better with results since an edge filter is used in the detection processing. The detection curve in this plot has the classic form of statistical signal processing detection theory but has significantly better performance (Pd >65% as Edge-MAD approaches 1.0). This is because the algorithm employs spatial correlation while statistical signal processing does not, and because some detections occur on internal structure that has stronger edges than the target boundary. The cuer false alarm rate was about 2 per image (~10^6 pixels), but many were due to image edge artifacts that will be corrected in future processing.

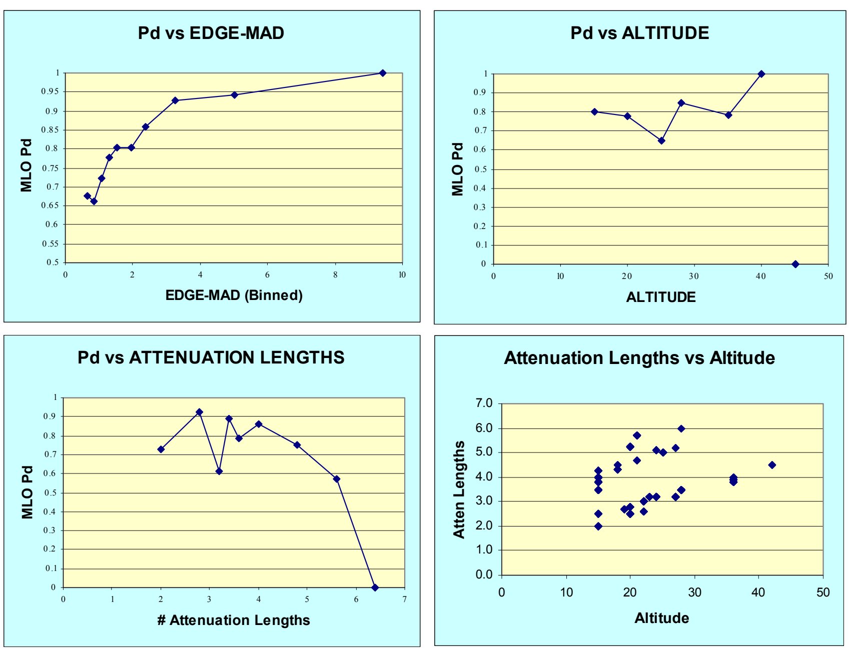

Figure3: The Cuer detection probability is robust

The other plots in *Figure 3* relate the cuer performance to important factors of the test environment - altitude and water column attenuation. These plots show that cuer performance has little dependence on altitude (because there are still sufficient pixels on target) but does begin to roll off at about five attenuation lengths. This rolloff occurs because of signal reduction with respect to the system noise level and is expected from the physics and the run geometry.

IMPACT/APPLICATION

A robust target cueing and identification capability developed under this project will have insertion potential into Navy minehunting and neutralization systems such as AQS-20A, RMS, AMNS, AUV/UUV applications, etc. Further development of the biological species ID capability provided by the Computer Vision Classifier has utility in environmental health surveys and species population and habitat studies.

TRANSITIONS

None to date. The algorithms developed will be offered on an as-needed/as requested basis to the AQS-20A program pending the results obtained from alternative approaches in upcoming field trials.

RELATED PROJECTS

OP52 – "EOID Model Validation and Performance Prediction". Tom Stefanick and Sam Osofsky of Metron are developing and validating models for EOID sensors and their operating environments to support system level imaging and target ID performance predictions

REFERENCES

The algorithms discussed herein have been developed under Raytheon proprietary and application-specific funding and as such do not have publicly available references. An exception to this is the "K-Means Clustering" algorithm which is a textbook segmentation approach in the digital image processing community.

There are multiple references discussing the foundation upon which the computer vision concepts detailed herein are developed. A list of references is available upon request.